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MAXIMISING PROFITS OF ELECTRICAL ENTITIES USING LOAD AND PRICE FORECASTING

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ABSTRACT

Load and Price forecasting are very essential to the operation of electricity companies. They enhance the energy-efficient and reliable operation of a power system. This paper focuses on a bidding strategy based on Short-Term Load Forecasting (STLF) technique presented in the deregulated electricity market. The bidding strategy in the deregulated market is an inherently difficult problem due to its characteristic property of volatility and load uncertainty. For years, it has been achieved by traditional stochastic approaches like time series but new methods based on artificial intelligence emerged recently in literature and started to replace the old ones in the industry. In order to follow the latest developments and to have a modern system, this thesis aimed to make a research on STLF using the Artificial Neural Network (ANN), Fuzzy and state estimation technique for forecasting the hourly electricity load and hence building up a strategy to bid in the market for the next 24 hours.

KEYWORDS: Load Forecasting, Price Forecasting, Maximizing Profits, Neural Networks, Fuzzy Logic

INTRODUCTION

Since the discovery of the light bulb, electricity has made a tremendous impact on the development of our society. Today, it is hard to imagine a life without it. To provide every factory and household with a sufficient supply of electric energy, electric companies were set up. They used to serve dedicated geographical areas from which consumers had to buy their electricity. Traditionally, centralized regulation of the electricity supply industry was considered necessary to ensure security of supply and efficient production. Efficiency was achieved through economics of scale. The power sector was characterized by a highly vertically integrated market structure with little competition. However, during the last two decades dramatic changes to the structure of the electricity business have taken place around the world.

The original monopolistic situation has been replaced by deregulated, competitive markets, where consumers, in principle, are free to choose their provider. To facilitate trading in these new markets, exchanges and pools for electric power have been organized. Everything from real-time and spot contracts to derivatives – such as (standardized, but not marked to market) forward, futures and option contracts – are traded. A power exchange, though, is not a necessity for a deregulated power market. In fact, in most countries the majority of deals – especially medium and long term – are made on a bilateral basis on the so-called over-the-counter (OTC) market. Nevertheless, it has been argued that the establishment of power exchanges has promoted competition and contributed to the high trading activity seen, for instance, in the Nordic market. Furthermore, the exchange serves as a source for updated, independent and good-quality market information.

In a competitive power market electricity can be bought and sold at market prices like any other commodity. As a consequence, the amount of risk borne by electric utilities, power producers and marketers has increased substantially.

Successfully managing a company in today's markets takes a fair amount of statistical analysis and educated guesswork. These in turn involve developing dedicated statistical techniques and managing huge amounts of data for modeling, forecasting and pricing purposes.

Unlike the analyses of random samples of observations that are discussed in the context of most other statistics, the analysis of time series is based on the assumption that successive values in the data file represent consecutive measurements taken at equally spaced time intervals. While this assumption is violated for a vast majority of financial data sets, it is fulfilled for power market data. Electricity spot prices, loads, production figures, etc., are sampled 24 hours a day, 365 days a year. This gives us a unique opportunity to apply statistical methods in the way they were meant to be used.

When electricity sectors were regulated, utility monopolies used short-term load forecasts to ensure the reliability of supply and long-term demand forecasts as the basis for planning and investing in new capacity. That is no longer the case where competition has been or is being introduced. The costs of over- or under-contracting and then selling or buying power on the balancing market have increased so much that they can lead to financial distress of the utility.

Minimization of volumetric risk has never been of such importance as it is today. As a result, load forecasting has gradually become the central and integral process in the planning and operation of electric utilities, energy suppliers, system operators and other market participants. Its position as one of the major fields of research in electrical engineering is not threatened as well since the financial penalties for forecast errors are so high that research is aimed at reducing them even by a fraction of a percent.

On the other hand, extreme price volatility, which can be even two orders of magnitude higher than for other commodities or financial instruments, has forced producers and wholesale consumers to hedge not only against volume risk but also against price movements. Price forecasts have become a fundamental input to an energy company's decision making and strategic development. As a result of the supply stack structure, load fluctuations translate into variations in electricity prices. However, an inverse relationship has been also observed. In some cases the issue of whether loads drives power prices, or vice versa, is not easily answered. Clearly, as they become partially co-determined, load and price forecasting could be treated as one complex task.

It is exactly the aim of this paper to present a common framework for modeling and forecasting these two crucial processes for every energy company. The statistical approach is chosen for this purpose as it allows for direct input of relevant statistical properties into the models. Furthermore, it is attractive because physical interpretation may be attached to the components of the models, allowing engineers and system operators to better understand the power market's behavior.

THE PROPOSED STRATEGY

The research work described in this paper is related to the maximize the profits of all the electrical entities of the electricity market. This paper aims at building a strategy for the participating entities to bid in the market based on the forecasted load and price. Generators can maximize returns by using electricity load and price forecasts to optimize generator availability in higher price periods and schedule maintenance during periods of lower price. Price forecasts are utilized by consumers to estimate energy costs for cash flow and budget planning and to lower electrical energy costs by scheduling consumption during lower priced periods.

Retail supply is the most competitive sector in the electricity supply industry with retailers earning returns on the margins between their purchase and sale prices of electrical energy. To survive in business the retailer needs to balance

having an attractive pricing package to attract customers and a price high enough to earn a return for stakeholders. Price forecasted in the paper is crucial for retailers to develop electrical energy purchase and pricing strategies that balance the requirements of customers and stakeholders.

EXPERIMENTAL RESULTS

The proposed method is used to forecast electricity load and bidding strategy is built to maximize the retailers profit in three different electricity markets: IEEE RTS data [11], New England Independent System Operator (NEISO) [12] and HSLDC (India) [13]. The IEEE RTS and NYISO data are selected as there has been wide research on these networks and Haryana State Load Dispatch Center data is chosen to present the practicality of the proposed method in the present Indian electricity market. The RTS data is IEEE standard data of load on hourly basis. The NEISO electricity market is deregulated and the system provides hour-and day-ahead forecasted electricity prices. The Haryana State Load Dispatch Centre conducts load forecasting for every 15 minutes.

Experiment I: Fuzzy Logic Technique

Results are presented for the RTS data, NEISO and Haryana datasets using fuzzy logic controller. Table 1 shows Error (ERR), Average Percentage Error (APE) and MAPE calculated for all datasets.

IEEE RTS Dataset

The dataset is modeled using the FLC rules. The results are obtained for forecasted load on hourly basis which is used to make the bids in the market. The difference between the actual and forecasted load result in the low or high bid made in the market. The MAPE and standard error estimate has been considered as the accuracy criterion to assess the forecasting performance of the models.

$$MAPE = \frac{1}{N} \frac{\left| \sum_{i=1}^{N} F_{forecast}^{i} - F_{Actual}^{i} \right|}{F_{Actual}^{i}}$$

Where $F_{forecast}^{i}$ and F_{Actual}^{i} are the forecasted and actual load at the hour interval N.

$$S_{FA} = \sqrt{\frac{\sum (F_{forecasted} - F_{Actual})^2}{N}}$$

Where S_{FA} is the standard error of estimate of forecasted load on actual load.

Further, this MAPE and S_{FA} are used as the accuracy criterion to assess the forecasting performance of the models. Based on the APE, the bids are made on the hourly basis so as to maximize the profit of the system. The bids are made in such a way that whenever the forecasted load is more than the actual load consumption, the load is saved for the time when the peak load occurs. The load is available for purchase in the electricity market at a high bid price when actual load is less than the forecasted load and the bid price is kept low when electricity is to be bought from the market participants. This bidding strategy aims to maximize the profits of each of the market participant in the deregulated market. For this data, the ERR of 7.34MW with S.D. (Standard Deviation) of 5.37 and APE of 9.82% with S.D of 8.99 are obtained. The MAPE is 9.82% with S_{FA} of 9.09. The worst hour is 6 with an ERR of 21.8MW and APE of 36.33%. The profit calculated for the market participants from the proposed bidding is 4025.7 Rs/MWh as shown in Figure 1.

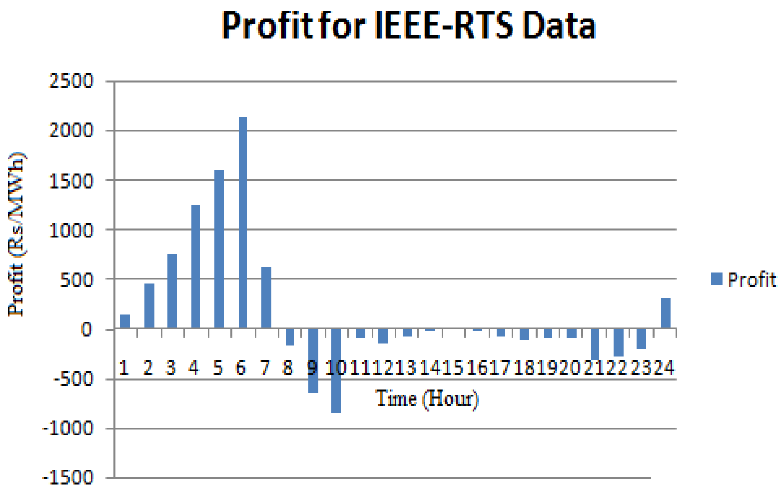

Figure 1: Profit for IEEE-RTS Dataset Using FLC

NEISO Dataset

The model is controlled based on the rules formed on hourly data from the NEPOOL region (courtesy ISO New England) from 2004 to 2007 and tested on out-of-sample data from 2008. The result obtained for NEISO data has ERR of 1624.12MW with S.D. of 965.62, APE of 11.67% with S.D. of 8.23. The worst hour during the day is 5 with ERR of 4025MW, APE of 33.61%. Figure 2 shows the benefits of the market participants. The MAPE of the data is obtained to be 11.67% and S_{FA} of 1879.19. It is clearly visible that with the bidding strategy built in consideration with the forecasted load gives a benefit of 287282.9 Rs/MWh.

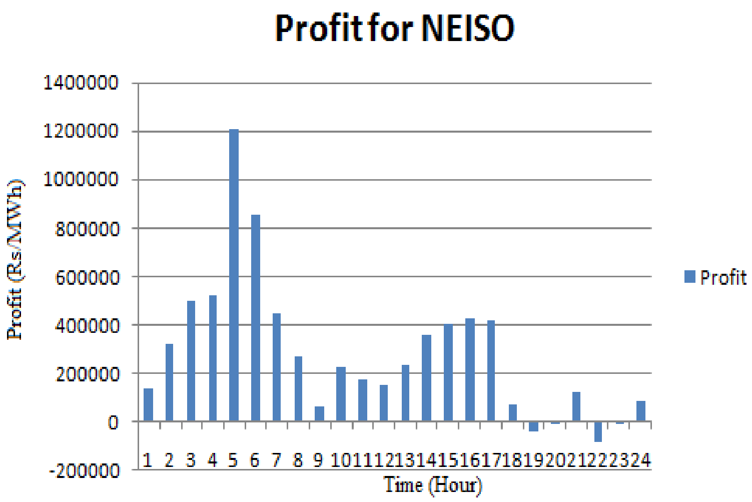

Figure 2: Profit for NEISO Electricity Market Using FLC

Table 1: ERR, APE and MAPE in RTS Dataset, NEISO and Haryana Electricity Markets

Hour	RTS Dataset		NEISO		Haryana	
	ERR(MW)	APE (%)	ERR(MW)	APE (%)	ERR(MW)	APE (%)
1	1.8	2.686567	1572	12.64886	357.47	1.773387
2	5.8	9.206349	2147	18.11356	876.83	4.24064
3	8.8	14.66667	2499	21.72855	669.61	3.27124
4	13.9	23.55932	2490	21.63336	381.42	1.889956
5	17.8	30.16949	4025	33.61169	147.22	0.705997
6	21.8	36.33333	3417	27.15569	1348.17	6.032574
7	7.8	10.54054	2299	16.7798	175.55	0.829022
8	4.2	4.883721	1422	9.754424	1084.49	4.910641
9	13.2	13.89474	600	3.896104	1347.41	6.029379

Table 1 Contd.,

10	14.2	14.79167	1917	11.91942	286.06	1.260951
11	10.8	11.25	1526	9.263081	121.42	0.539131
12	7.3	7.684211	1385	8.335841	1063.25	4.983186
13	4.8	5.052632	1574	9.582369	3414.92	17.98739
14	1.2	1.263158	1819	11.24158	3388.03	17.82051
15	0.8	0.860215	2031	12.71839	1909.75	9.320286
16	0.2	0.212766	2031	12.71839	3279.75	17.15328
17	5.2	5.252525	2049	12.84559	1584.18	7.610462
18	6.3	6.3	825	4.803493	941.41	4.387101
19	6.3	6.3	491	2.655346	4201.51	23.08714
20	2.2	2.291667	16	0.088968	140.48	0.631101
21	6.8	7.472527	1010	5.944673	81.42	0.362166
22	5.1	6.144578	1042	6.881522	713.97	3.480409
23	4.2	5.753425	92	0.648253	1352.74	6.395105
24	5.8	9.206349	700	5.223881	628.59	3.077011
MEAN	7.345833	9.824019	1624.125	11.6747	1228.985	6.157419
S.D.	5.47238	8.993159	965.6213	8.237625	1192.067	6.41207
S_{FA}	9.09		1879.19		1694.76	
Profit (Rs./MWh)	4025.7		287282.9		4933876	

Haryana State Load Dispatch Centre Dataset

For HSLDC electricity market, data of May 2013 is selected. The results for this data are shown in Table 1. The average ERR for the day is 12228.98MW with S.D. of 1192.067 and APE of 6.15% with S.D. of 6.41. The MAPE is 6.15 with S_{FA} of 1694.76. The profit of the whole day from the bidding strategy is 4933876 Rs/MWh which is very high as shown in Figure 3.

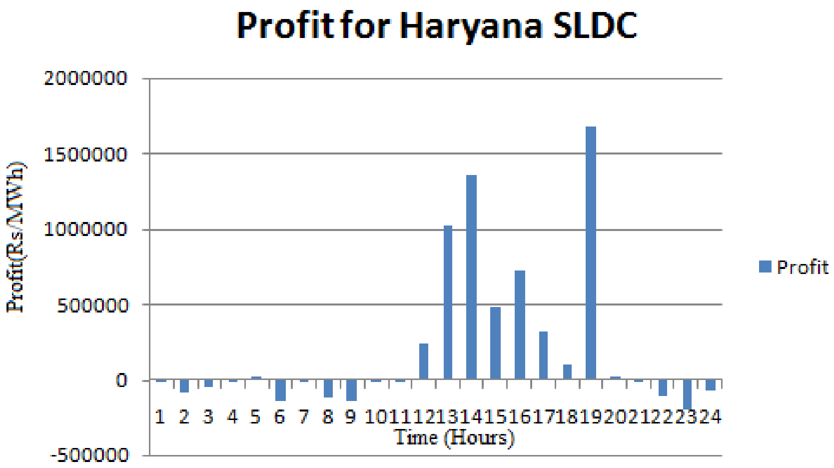

Figure 3: Profit of Haryana SLDC Dataset Using FLC

Experiment II: ANN Model

This section will describe training and test data used to test the proposed ANN model for short-term load forecasting and making the bidding strategy in the deregulated market.

Training and Test Data

Load and weather data are used for training and tests for the ANN model. Daily load data comprises of hourly loads, and daily weather data comprises of the hourly temperatures of the day.

Table 2: Training and Test Sets

Season	Training Sets		Test Sets	
	Weeks	No. of Input Vector	Weeks	No. of Input Vector
Winter	1-9&44-47 January, February, November	91	48-52 December	28
Spring/Fall	10-17&40-43 March, April, October	84	36-39September	28
Summer	18-22&27-30 May, July	63	23-26June	28

One month in each season will be used as a test set, based on the load in that particular month. For winter, December or week 48 to week 52 will be the test set, since the yearly maximum load occurs on week 51. For summer, the test set will be the month of June or week 23 to week 26, since the summer maximum load or the second highest load during a year occurs on week 23. For fall, the month of September, that is weeks 36 to 39, are chosen for the test set, since the yearly minimum load occurs on week 38. Each seasonal model will have a different number of training vectors, which will result in different processing times for training and different errors produced by each model.

Stopping Criteria for Training Process

Stopping criteria for the training process are based on the error produced by ANN. To determine the error, the APE, MAPE and S_{FA} are used.

Each model is trained with its training sets for a certain amount of epoch (iterations). After the maximum number of epochs is reached, the model is tested by the training set. Based on test results, APE and MAPE can be calculated. If the calculated MAPE is higher than 3%, retraining must be done. This process continues until all MAPE from test results are below 3%.

IEEE-RTS Dataset

The RTS load data is followed for hourly peak percentages. With the available data, the ANN model is trained and tested using the feed-forward back propagation algorithm. Due to its special features, the algorithm resulted in a very fast training, and the error is significantly reduced to very low value. The performance analysis shows the MAPE of 1.35% and regression accuracy of 99.74%. The forecasted load is used to make the bidding strategy as described in earlier section. The ERR is 8.17 MW with S.D. of 10.99 and APE is 9.54% with S.D. of 12.84. The profit of 13702.96 Rs/MWh (Figure 4) is obtained for the complete day after load management.

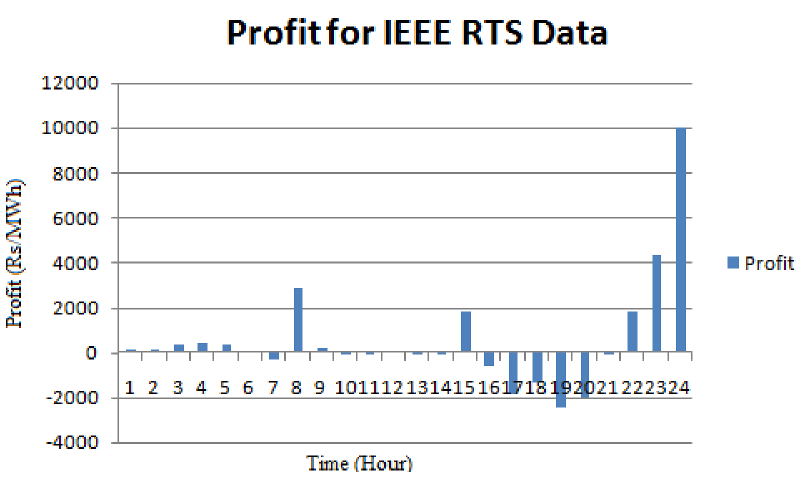

Figure 4: Profit of IEEE-RTS System Using ANN Technique

Table 3: ERR, APE and MAPE in RTS Dataset, NEISO and Haryana Electricity Markets

Hour	RTS Dataset		NEISO		Haryana	
	ERR(MW)	APE (%)	ERR(MW)	APE (%)	ERR(MW)	APE (%)
1	0.7589	1.132687	3.2366	0.026043	2.297	0.011395
2	0.7234	1.148254	3.3737	0.028463	3.5065	0.016959
3	1.4603	2.433833	73.5312	0.639346	6.2521	0.030543
4	1.6381	2.776441	2174.541	18.89262	670.3654	3.321696
5	1.3223	2.241186	2585.208	21.58838	1494.756	7.168139
6	0.4177	0.696167	3502.427	27.83459	1176.902	5.266212
7	3.0562	4.13	2789.764	20.36176	906.1602	4.279276
8	9.5407	11.09384	1847.164	12.6709	267.1578	1.209708
9	0.9872	1.039158	793.5441	5.152884	338.5679	1.515021
10	0.7917	0.824688	65.8989	0.409743	162.8473	0.71783
11	0.801	0.834375	708.9245	4.303293	1182.785	5.251821
12	0.2575	0.271053	1913.823	11.51865	2323.761	10.89089
13	1.2255	1.29	1628.318	9.913055	134.7578	0.709809
14	0.1845	0.194211	844.5424	5.219346	1804.544	9.49162
15	5.2035	5.595161	799.4066	5.00599	1990.608	9.714905
16	8.724	9.280851	1698.015	10.63319	1396.616	7.304384
17	26.1797	26.44414	2522.755	15.81565	301.839	1.450046
18	18.7549	18.7549	2334.832	13.59436	977.1968	4.553872
19	34.7008	34.7008	3896.647	21.07321	4357.942	23.94672
20	29.1543	30.36906	2072.071	11.52174	138.4853	0.62214
21	0.1071	0.117692	2423.521	14.26439	673.8188	2.997225
22	7.1711	8.63988	4213.327	27.82544	1556.243	7.58626
23	14.3661	19.67959	5103.201	35.9583	714.142	3.376121
24	28.5658	45.34254	5308.768	39.61767	1061.872	5.197971
MEAN	8.170513	9.542938	2054.452	13.91121	985.1427	4.859607
S.D.	10.99036	12.84232	1538.086	11.0776	986.1462	5.242401
S_{FA}	13.50		2547.137		1379.30	
Profit (Rs./MWh)	13702.96		155709795		45659286	

NEISO Dataset

The model is trained using neural network formed on hourly data from the NEPOOL region (courtesy ISO New England) from 2004 to 2007 and tested on out-of-sample data from 2008. In spite of using less training data, the result obtained for NEISO data has ERR of 2054.44 MW with S.D. of 1538.08, APE of 13.91% with S.D. of 11.07. Figure 5 shows the benefits of the market participants. The MAPE of the data is obtained to be 13.91% and S_{FA} of 2547.137. The regression accuracy is 99.99%. It is clearly visible that with the bidding strategy built in consideration with the forecasted load gives a benefit of 155709795 Rs/MWh.

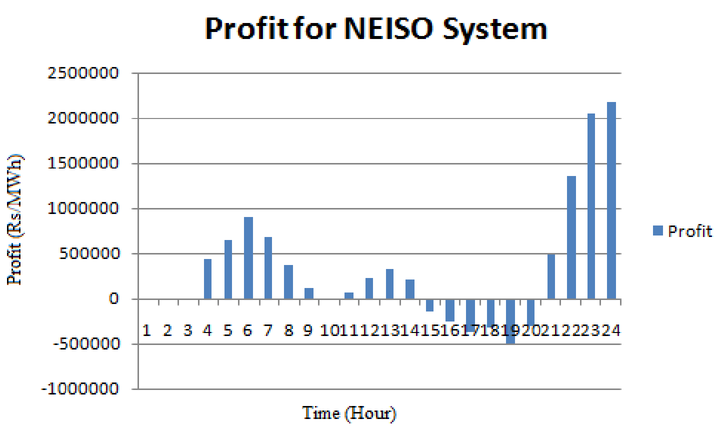

Figure 5: Profit of NEISO System Using ANN Technique

Haryana State Load Dispatch Centre Dataset

The regression accuracy of 100% is obtained with MAPE of 4.85%. The average ERR for the day is 985.1427 MW with S.D. of 986.1486 and APE of 4.85 % with S.D. of 5.24. The S_{FA} is obtained to be 1379.30. The profit of the whole day from the bidding strategy is 45659286 Rs/MWh which is very high as shown in Figure 6.

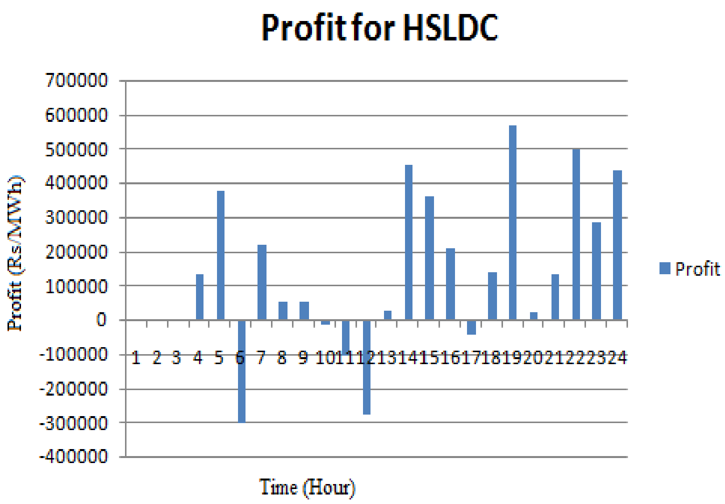

Figure 6: Profit of HSLDC System Using ANN Technique

Comparison of Fuzzy and ANN Technique

It can be clearly seen that the ANN technique gives much more accurate results as compared to fuzzy technique because of the feed forward back propagation algorithm. The social benefit of the market is also more in case of ANN technique.

CONCLUSIONS

The strategy to bid in the deregulated electricity market is essential to facilitate the maximum profit to the market participants. Though many research carried out in this field, significant improvements are yet to be performed. The bidding strategy is proposed using fuzzy and ANN techniques using the historical data. The analysis is done on three datasets and their profits are calculated. Bids are made in the range 50-400 Rs/MWh which depends on the forecasted load. The bids are made high if the retailer has more load to supply to the customer and vice versa. The results of error analysis and profits for the three datasets: IEEE-RTS, NEISO and Haryana SLDC are shown which proves that the proposed strategy results in the profit of all the systems.

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